

ORIGINAL ARTICLE

Artificial Intelligence and the Trainee Experience in Radiology

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Abstract

The hype around artificial intelligence (AI) in radiology continues unabated, despite the fact that the exact role AI will play in future radiology practice remains undefined. Nevertheless, education of the radiologists of the future is ongoing and needs to account for the uncertainty of this new technology. Radiology residency training has evolved even before the recent advent of imaging AI. Yet radiology residents and fellows will likely one day experience the benefits of an AI-enabled clinical training. This will offer them a customized learning experience and the ability to analyze large quantities of data about their progress in residency, with substantially less manual effort than is currently required. Additionally, they will need to learn how to interact with AI tools in clinical practice, and more importantly, understand how to evaluate AI outputs in a critical fashion as yet another piece of information contributing to the interpretation of an imaging examination. Although the exact role AI will play in the future practice of radiology remains undefined, it will surely be integrated into the education of future radiologists.

Key Words: Artificial intelligence, radiology education, radiology residency

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INTRODUCTION

A great deal of attention is being paid to artificial intelligence (AI) in radiology, and with it comes a substantial amount of uncertainty and hype. Exactly what role AI will play in the future practice of radiology remains undefined. As a result, there is also uncertainty about how it will affect radiology residency training. Nevertheless, there are many potential ways AI could be used to teach future radiologists. The recent attention paid to AI and its capacity to detect imaging

findings has measurably affected medical students' perception of the field [1-3]. Framing the discussion of how AI will affect the trainee experience in the context of how radiology residents and fellows are taught today may serve to reassure future radiology residents that they will have a meaningful career augmented by AI.

CURRENT APPROACHES TO RADIOLOGY EDUCATION

The ACGME has substantial oversight of radiology resident education and has a set of common requirements for all residency programs. One of the goals implicit in the requirements is to facilitate the development of resident knowledge, skills, and values required to take ownership of patient care [4]. ACGME requirements specific for radiology resident education, how residency programs may satisfy those requirements, as well as some educational trends in providing residents with educational resources, didactics, workday teaching, and feedback will be discussed.

Educational Resources

ACGME requires that all radiology residency programs have sufficient learning resources available to trainees [1]. This includes readily available access to specialty specific material in electronic or format that must be able to support the number of residents within the radiology residency program. Radiology residencies can achieve this

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107 in several ways including purchasing literature, online
 108 resources, and providing access to university libraries.
 109

110 Learning materials are conventionally in the form of
 111 textbooks, though review articles, online self-assessment
 112 platforms, and educational videos have been growing in
 113 popularity and may be preferred by some residents [5]. Most
 114 residency programs provide textbook recommendations and
 115 chapter-specific assignments for each rotation. However,
 116 reading, rereading, and highlighting textbooks may be a less
 117 effective form of learning [6,7]. This could be improved
 118 when reading becomes a more active process, whereby
 119 learners self-quiz, pause to consolidate information, and
 120 contrast disease processes [8-10]. Educational videos may be
 121 more useful to some learners and are becoming increasingly
 122 available from both radiology societies and commercial
 123 entities. Videos under 15 min have been growing in
 124 popularity due to their limited scope, which may make
 125 the information feel more digestible. Review articles are
 126 preferred by some residents due to ease of online access
 127 [11]. As a result, some residency programs provide not
 128 only textbook-specific reading recommendations but also
 129 suggestions for resident-appropriate video content and
 130 article collections.

131 Testing and retrieval-based strategies, in comparison
 132 with textbook reading, have been shown to be more effective
 133 in improving knowledge retention. Online question banks
 134 are growing in popularity both for learning and resident
 135 assessment [12]. Online platforms in comparison with
 136 textbooks and articles are also more dynamic. These
 137 learning platforms allow for the creation of curated case
 138 sets to meet the educational needs of a learner. Cases can
 139 be arranged by subspecialty, modality, or disease process
 140 depending on learner needs. Online platforms also
 141 interleave cases that users have previously answered
 142 incorrectly, increasing the likelihood that users address
 143 knowledge deficiencies [13].

144 Radiology residency programs are also required by the
 145 ACGME to have rotation-specific goals and objectives that
 146 are readily available to all residents [1]. These can be
 147 institution specific or adopted and modified from national
 148 societies. For instance, the American Society of Thoracic
 149 Radiology has published learning guidelines for residents
 150 rotating through cardiothoracic imaging. The guidelines
 151 are comprehensive and structured, providing programs
 152 that may not have robust subspecialty imaging sections
 153 guidance from experts in the field.

154 Didactics

155 Protected didactic time for residents in training is required
 156 by the ACGME. It is expected that residents participate in
 157 structured didactic activities, which are broadly defined and

159 can include lectures, conferences, asynchronous learning,
 160 simulations, and case discussions [1]. Most residency
 161 programs provide a daily lecture series, with topics divided
 162 among radiology subspecialties. Lectures are often 45 to
 163 60 min and delivered as a slide presentation. This
 164 approach can be powerful when used effectively. However,
 165 presentations run the risk of being text-heavy, leading
 166 some lecturers to read directly from slides with little audi-
 167 ence participation. Attention of learners typically wanes
 168 when content is delivered in this fashion, and knowledge
 169 retention also tends to be poor compared with other
 170 learning methods [14,15].

171 Lectures can be redesigned to increase learner retention
 172 and understanding [16-19]. The flipped classroom assigns
 173 trainees a prelearning assignment before the didactic, such
 174 as an article or video. In class, participants have the
 175 chance to apply learned concepts from the prelearning
 176 under the instruction of the lecturer. This process allows
 177 for corrective feedback from an expert and the chance for
 178 learners to flush out concepts. It also gives them an
 179 opportunity to learn from and teach their peers. Applying
 180 the flipped classroom to medical students rotating through
 181 a radiology clerkship has shown promise. Although there
 182 were no baseline differences in test scores between
 183 students in the flipped classroom and traditional lectures,
 184 flipped learning was associated with greater task value,
 185 increased academic achievement, and more positive
 186 emotions [20].

187 Software has also been developed that may lead to more
 188 engaging lectures. Polling software can seamlessly integrate
 189 with slide presentations and provide a real-time, graphical
 190 representation of answer choices for questions posed to the
 191 audience. The RSNA Diagnosis Live application (<https://live.rsna.org/>) allows speakers to upload images so that
 192 participants can answer questions on their personal devices
 193 as well as interact with radiology images by selecting the
 194 abnormality [21,22]. Commercial tools also exist for either
 195 computers or tablets that simultaneously allow the speaker
 196 and one or more participants to draw on the lecturer's
 197 slides from separate devices [23]. This can be particularly
 198 helpful for case conferences, where residents can circle or
 199 outline abnormalities.

200 Learning During the Workday

201 ACGME requires that a sufficient number of faculty be
 202 present to instruct and supervise all residents [4]. These
 203 faculty members must be role models of professionalism,
 204 demonstrate strong interest in resident education, and
 205 administer and maintain an educational environment
 206 conducive to educating residents [4]. Learning from
 207 faculty during the workday is usually more experiential

and mainly occurs when residents review examinations under the guidance of an expert radiologist at a PACS reading station. Learning in this setting is influenced by two elements: the educational ability of the supervising radiologist in conjunction with resident learning preference and the cases that are available for interpretation. Pairing of residents with an attending radiologist may be arbitrary and dictated by work schedules rather than educational styles and personalities. Some attention is usually given to resident case mix and work volume, although resident case exposure is usually driven by worklist assignments developed for predominately clinical rather than educational needs. ACGME does have a required minimum number of modality-specific cases to be logged for residents over the course of their training [24].

During a rotation, a resident may be instructed to focus on studies that ready them for call (pulmonary embolism, traumas, stroke alerts) or a modality that they have graduated to (MRIs). Work volume expectations may also be set. However, both volume and case mix are determined by referring providers and the imaging center's capacity. Surveillance oncologic imaging may represent the majority imaging during the workday, limiting residents' exposure to other disease processes as well as the supervising radiologist's ability to address potential educational deficiencies. Radiology worklists are also limited in their ability to parse out interesting or potentially educationally noteworthy studies that could foster discussion and resident assessment. As a result, residents may not encounter some diseases or imaging modalities frequently enough to feel proficient.

Radiology residencies have tried to address this by creating teaching files arranged by modality, specialty, or disease process. Radiology case-based simulations have been developed to round out resident experiences and call preparedness. Vendor-neutral digital teaching files allow radiologists to upload anonymized imaging studies from PACS with minimal disruption to clinical workflow [25]. Cases can be labeled, grouped into decks, and authored to highlight relevant teaching points. Case-based simulations in preparation for call have been shown to at least create a subjective feeling of preparedness for trainees [26].

Resident Evaluation and Feedback

The ACGME requires training programs to maintain a learning environment conducive to educating residents in each of the six core competencies: professionalism, patient care and procedural skills, medical knowledge, practice-based learning and improvement, interpersonal and communication skills, and systems-based practice [4]. These core competencies provide a framework in developing

physicians entrusted to enter autonomous practice. Residency-specific milestones were created to assess residents' trajectory during their training in each of these six competencies and are used during ACGME-required clinical competence committee's semi-annual review of resident performance [27]. Milestone performance data for each program's residents are an element used in the ACGME's Next Accreditation System to assess if residents are progressing and identify which residency programs are flourishing or struggling [28]. Information from this national database can identify programs that are doing well to help establish best practices and provide aid to those having difficulty [29].

During their training, residents may progress through five levels of milestones for each core competency. These levels do not necessarily correspond to years of training, such that a third-year resident does not have to be a level 3, and a junior resident may be at a higher milestone compared with a senior. Residents could also regress in milestone levels. Level 4 is designated as a graduation goal but is not a requirement for graduation, which is at the purview of the residency program director. Level 5 is considered to be an expert resident who has surpassed expectations.

Core competencies are further divided into subcompetency categories. For instance, "Patient Care" has four subcompetency categories (reporting, clinical consultation, image interpretation, and competence in procedures) and systems-based practice has eight, each with five levels of milestones. Each milestone level has language specific for the subcompetency being assessed. For example, in level 1 of the subcompetency "Diagnostic Knowledge," the resident "demonstrates knowledge of imaging anatomy," whereas in level 5, the resident "proficiently integrates knowledge of anatomic and molecular imaging with pathophysiology to formulate a diagnosis at the expected level of a subspecialist." An updated version, Milestones 2.0, took effect in July 2020.

HOW AI MIGHT CHANGE THE RADIOLOGY TRAINEE'S EXPERIENCE

AI-Enabled Radiology Education

The future impact of AI in radiology is not limited to its role in findings detection or its potential impact on workflow efficiency [30]. AI also has the potential to take large quantities of data about resident education, performance, and progress through training and enable customization of the educational experience to the strengths and weaknesses of the individual trainee [31,32].

As newer educational methods permeate radiology (eg, flipped classrooms, virtual education), incorporation of AI into education delivery can offer new methods for residents

315 to learn clinical radiology. For example, as the concept of
 316 gamification becomes a part of radiology education [33],
 317 trainees can earn rewards in an online platform for
 318 completing activities, such as achieving ACGME
 319 milestones, interpreting certain numbers or types of
 320 examinations, or passing online educational modules. AI
 321 can be a useful adjunct in helping residents to track their
 322 progress through training, by automatically identifying
 323 activities that are completed or milestones that are
 324 achieved and logging these for each trainee. At present,
 325 the logging process tends to be entirely or almost entirely
 326 manual, and adds work for each individual resident to
 327 keep track of their completed activities [34,35].

328 In addition, many radiology residency programs provide
 329 feedback to residents on the discrepancies between their on-
 330 call interpretations and the final attending overread [36,37].
 331 This feedback may take the form of a message back to the
 332 interpreting resident that is manually entered by the
 333 faculty member or a text tag inserted in the report that
 334 can be mined and sent to a summary dashboard.
 335 Regardless of the form, the information is intended to
 336 provide residents with the opportunity to review cases on
 337 which they missed or misinterpreted findings and provide
 338 a valuable learning opportunity. By analyzing radiology
 339 resident performance using AI, there is greater potential to
 340 provide personalized resident feedback on either the basis
 341 of daytime rotation performance or off-hours call perfor-
 342 mance. Discrepancies with respect to the final attending
 343 interpretation can be analyzed to identify trends that could
 344 be aligned with the types of errors that typically occur in
 345 reports [38]. In turn, these could be summarized across
 346 residents to provide a number of relevant cases for review.
 347 Residents have often expressed concern that the feedback
 348 they receive is graded inconsistently; for example, one
 349 radiologist's major discrepancy may be another's minor
 350 discrepancy [39]. AI can potentially standardize resident
 351 feedback by analyzing large volumes of historic
 352 discrepancy data and providing guidance to both trainees
 353 and faculty.

354 In addition to analysis of on-call interpretations, AI built
 355 into the dictation system could be used to identify areas of
 356 uncertainty that residents encounter while interpreting ex-
 357aminations during daytime rotations. Furthermore, this in-
 358formation could be used to tailor the types of examinations
 359 that a resident interprets by incorporating it into the reading
 360 work list [40]. For example, a resident who needs more
 361 experience with interstitial lung disease cases could
 362 preferentially receive these chest CTs on a given workday.
 363 Similarly, on a musculoskeletal radiology rotation, this
 364 would even out the distribution of joint cases and spine
 365 cases, such that the former is not preferentially dictated by
 366 the fellows, and the latter by the residents.

AI-Powered Radiologist Decision Support

367 Although a great deal of attention is focused on clinical
 368 decision support for physicians ordering imaging, consider-
 369 ably less attention is focused on radiologist decision sup-
 370 port at the time of diagnosis. This conventionally takes the
 371 form of guidance regarding follow-up recommendations for
 372 lesions identified during interpretation of images [41];
 373 however, AI could supply diagnostic support for both
 374 practicing radiologists and radiology trainees taking
 375 independent call [42]. One example of this is the use of
 376 Bayesian networks to offer differential diagnoses based on
 377 a set of described findings [43].

AI-Enabled Assessment of Radiology Trainees and Radiologists

378 In light of changes to the ABR licensure process for diplo-
 379 mates over the past decade, the potential role of AI in
 380 evaluating radiology trainees' preparedness for independent
 381 call and independent practice should also be considered.
 382 One study in the literature correlates USMLE examination ^{Q6}
 383 scores with the likelihood for subsequent poor performance
 384 on the ABR examinations [44]. However, more real-time
 385 assessment of residents during their training would be
 386 extremely valuable for identifying areas for further
 387 improvement in advance of sitting for licensure examina-
 388 tions. In the future, one could envision adaptive examina-
 389 tion of radiology trainees that is driven by AI to not only
 390 adjust to the level of knowledge of the candidate, but also to
 391 re-evaluate areas that may have previously been remediated
 392 [12]. Similar approaches could be applied for maintenance
 393 of certification as is currently required by the ABR [45].

Teaching Radiology Residents About AI

393 In addition to considering how AI will change the trainee
 394 experience, it is important to consider how, when, and to
 395 what extent we should teach radiology residents and fellows
 396 about AI itself. The literature suggests that at minimum,
 397 radiology trainees will need to know how to use AI in their
 398 clinical work to understand where it can play a role and how
 399 to interpret its output [46]. One survey of current radiology
 400 residents and faculty found that nearly 85% of respondents
 401 felt that an understanding of AI should be taught during
 402 residency, and 80% felt it was as important to learn as
 403 imaging physics [47]. Another survey of practicing
 404 radiologists showed that they did not feel like they knew
 405 enough about AI and also wanted to learn more, so they
 406 might also benefit from the same education provided to
 407 trainees [48]. The challenge in adding more required
 408 components to the radiology residency arises when
 409 deciding what to remove or shorten to make room in the
 410 curriculum for new knowledge. Radiology residents will
 411

likely need to be exposed to AI-related education throughout residency, ideally in the form of dedicated sessions as well as integrated into clinical teaching, as is currently done with medical physics.

Potential Adverse Effects of AI

As with every new technology, there will be potential adverse effects of AI that need to be addressed proactively. One popular proposed use for AI is triaging cases with abnormalities to the top of the radiologist's worklist, or having AI label normal examinations as such and remove them from the worklist entirely [49,50]. Although there are obvious efficiency benefits associated with removing normal cases from the worklist [49,51], the impact on radiology training should not be ignored. Radiology residents learn how to identify abnormalities by first establishing a mental standard for the normal appearance of a particular organ when captured by a particular imaging modality. Diverting these cases away from residents early in their training will thwart the normal learning process that radiology residents experience and require this knowledge to either be imparted in a different way or to limit junior residents' exposure to AI triage tools. Another option would be to first teach junior residents the traditional methods of image interpretation before exposing them to AI; however, the practicality of this approach would have to be balanced against the pervasiveness of AI in clinical practice.

A new challenge in training future radiologists will be teaching residents and fellows to recognize AI errors [50-52]. At present, evaluating software postprocessing of reconstructed images is primarily limited to reviewing measurements; these are generally easily recognized with training. However, AI errors may be more subtle, less predictable, and less repeatable, given the nature of the technology [52]. Susceptibility to automation bias—the idea that the computer is more correct than the human by virtue of being a machine—is greater when the human practitioner is less confident, and it could have a stronger impact on less experienced radiologists and radiology trainees [53]. Future radiology trainees will be taught to be mindful of automation bias, just as they currently learn to be wary of satisfaction of search [54,55].

In conclusion, as with new imaging modalities, PACS, and structured reporting, AI will undoubtedly require changes to radiology trainee education. However, there are many opportunities to integrate AI into the existing pathways for radiology residents and fellows. AI will be yet another noninterpretive skill that radiology residents will be required to know. Current and future radiology residents and fellows will need to know how to interpret AI outputs,

in addition to knowing how to interpret images. They will need to understand how AI modifies the clinical workflow and be sensitive to AI outputs that seem unusual or incongruent. Although exactly what role AI will play in the future practice of radiology remains undefined, it will surely be integrated into the education of future radiologists.

TAKE-HOME POINTS

- Current educational approaches for radiology trainees include recommended readings, live and recorded lectures, and teaching at the workstation. Newer techniques such as flipped classroom sessions and polling can be used to enhance learning and the learner experience.
- AI has the potential to take large quantities of data about resident education, performance, and progress through training and enable customization of the educational experience to the strengths and weaknesses of the individual trainee.
- AI could supply diagnostic support for both practicing radiologists and radiology trainees taking independent call.
- Current and future radiology residents and fellows will need to understand how data should be curated for AI development, how AI tools can be developed, and how to interpret AI outputs, in addition to knowing how to interpret images.
- The radiologists of the future will need to understand how AI modifies the clinical workflow and be sensitive to AI outputs that seem unusual or incongruent.

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